Misallocation, Access to Finance, and Public Credit: Firm-Level Evidence

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Using a database of 23,000 firms in 45 economies, we test the quantitative importance of access to finance and access to public and private credit for the determination of misallocation. We first derive measures of factor market and size distortions, and then use these measures within a regression framework to test the significance of self-declared access-to-finance obstacles as well as the effect of access to a credit line issued by either a government-owned or private bank. We find that access-to-finance obstacles and private credit increase the dispersion of distortions. Public credit has a very small effect. For firms that do not face financial obstacles, public credit increases the dispersion of distortions; for firms that face financial obstacles, it slightly decreases dispersion. Public credit does not appear to compensate for the distortions that exist in private credit markets. Quantitatively, however, financial variables explain a very small part of the dispersion of factor market and size distortions.

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I. Introduction

Recent literature has emphasized the role of misallocation in determining total factor productivity (TFP) differences between economies. Misallocation implies that aggregate TFP could be higher given the same amount of capital, labor, and firm-level TFP. Because of distortions that prevent factors of production from being allocated for their best use, firms with high productivity may be too small and firms with low productivity may be too large, leading to a fall in aggregate (weighted) TFP. One of the key distortions that may cause misallocation is the existence of financial access problems that generate quantity constraints and price dispersion in credit markets. In order to bypass these financial access distortions, governments often resort to public policies for the allocation of credit through government-owned credit institutions.

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In this paper, we test empirically the quantitative importance of access-to-finance obstacles, access to public and private credit, and their interaction, for the determination of the dispersion of distortions. Using a database of around 23,000 firms in 45 economies, we first derive measures of factor market and size distortions from the theoretical framework proposed by Hsieh and Klenow (2009).[1] In this framework, the dispersion of distortions determines the degree of misallocation, and thus TFP losses, at the aggregate level. We then use these distortion measures and, within a regression framework, test the significance of self-declared access-to-finance obstacles as well as the effect of access to a credit line issued by either a government-owned or private bank. Since selection to receive a public and/or private credit line may be endogenous, we instrumentalize these variables. Then, using a factor representation of the regression results, we obtain a decomposition of the contribution of these variables to the dispersion of factor market and size distortions in order to assess whether these variables increased or decreased the dispersion of observed distortions.

Our key results are as follows. Access-to-finance obstacles increase the dispersion of both factor market distortions and size distortions. Private credit also significantly increases the dispersion of both distortions, especially the size distortion. This is an expected result since the existence of informational asymmetries in underdeveloped financial markets can lead to an inefficient allocation of private credit. Public credit, on the other hand, has a very small effect. For firms that do not face financial obstacles, it increases slightly the dispersion of both distortions. For firms that face financial obstacles, it decreases slightly the dispersion, but it is not significant in the case of size distortions. Public credit does not appear to compensate for the distortions that exist in private credit markets. Overall, however, a large part of the dispersion of distortions remains unexplained. Financial variables appear important only in driving the explained part of these distortions and are significant. Quantitatively, they explain too small part of them to be considered as the key drivers of misallocation.

Our study only looks at the effects of these variables through the misallocation channel and not through other direct channels that affect productivity and capital accumulation. Also, we are only looking at the misallocation effects and ignoring the cost of setting up and running government-owned credit institutions and the cost of subsidizing credit through taxes. In this respect, our study uncovers another channel through which credit policies can affect aggregate outcomes. Nevertheless, it is an important one given the potential TFP gains from reallocation. Government-owned credit institutions are common in many emerging markets and imply costly operations. Banks such as the China Development Bank in the People's Republic of China (PRC), the Brazilian Development Bank and Caixa Economica in Brazil,

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[1] The total number of economies in the sample is 45. In many of the empirical measures, however, economies are dropped due to the unavailability of certain variables.

Bancoldex in Colombia, and a large number of state-owned banks in India are examples of the proliferation of credit institutions with an important element of government ownership and/or explicit development goals.

A. Related Literature

Our paper is related mainly to two strands of existing literature. On one hand, there is a growing body of theoretical and empirical literature on misallocation. On the other hand, there is a strand of literature analyzing the effects of public credit and development banks. The role of misallocation has been emphasized in the seminal works of Hopenhayn (1992) and Hopenhayn and Rogerson (1993), with further contributions from Banerjee and Duflo (2005); Restuccia and Rogerson (2008); Guner, Ventura, and Xu (2008); and Bartelsman, Haltiwanger, and Scarpetta (2013). An important work for our research is Hsieh and Klenow (2009), which develops a method to measure how distortions at the micro level imply aggregate TFP losses and uses this method to quantify TFP losses in the PRC and India relative to the United States (US). Their findings show that, had the PRC and India had similar levels of misallocation to the US, their TFP would be between 30% and 60% higher, respectively. Kalemli–Ozcan and Sorensen (2012) use a similar approach to ours by investigating the role of access to finance for misallocation in African economies. However, they do not analyze the effect on the dispersion of distortions or focus on the role of private and public credit.

The role of distortions to capital and credit markets in determining misallocation has attracted increasing interest in recent years. Midrigan and Xu (2014) report that the dispersion of the marginal product of capital is of an order of magnitude several times larger than that for the marginal products of labor and intermediate inputs. Furthermore, this dispersion is very persistent, which implies that capital adjustment costs cannot be the sole source of misallocation. Since financial systems channel funds from less to more productive projects, a lack of financial development can hinder TFP. Banerjee and Duflo (2005), for example, provide evidence on the role of credit constraints and other credit market imperfections in misallocation and, hence, productivity differences across economies. However, the literature on the relationship between finance and misallocation is far from settled. Moll (2014) shows that in a simple setting where firms face collateral constraints à la Kiyotaki and Moore (1997), if productivity shocks are persistent, then misallocation losses can be large and disappear only slowly. On the other hand, they are unimportant in steady state. This is because firms facing persistent shocks can use self-financing as a form of insurance against incomplete access to credit markets. Banerjee and Moll (2010) argue, however, that misallocation can still exist in steady state at the extensive rather than intensive margin (through the firm entry and exit channel). Buera, Kaboski, and Shin (2011), using a quantitative model with financial frictions, find that they account for around

50% of TFP gaps between economies. The mechanism is that firms with larger scales of operations are more productive and have more financing needs, thus financial frictions affect them disproportionately. However, Midrigan and Xu (2014), using firm-level data for the Republic of Korea, find that financial frictions have a quantitatively small effect on misallocation. This is consistent with the micro evidence reviewed by Udry (2011), who finds that financial constraints do not play a dominant role in determining misallocation.

Our paper also relates to the literature on the role of public credit and government-owned banks for development. Early empirical literature such as La Porta, Lopez de Silanes, and Shleifer (2002) find a negative effect of public ownership of banks on subsequent productivity growth. Carvalho (2014), using firm-level data for Brazil, finds that public credit is directed to shifting employment toward politically attractive areas before elections. Ribeiro and de Negri (2009), using firm-level data for firms accessing credit from the Brazilian Development Bank, find very limited effects of public credit on TFP levels and growth. Banerjee and Duflo (2014) use a policy change in India that modified eligibility for directed credit and find that public credit was used to expand economic activity rather than substitute for other forms of credit. This is interpreted as evidence that firms were credit constrained before accessing public credit. Eslava, Maffioli, and Meléndez (2014) also find that access to financing from a nontargeted, unsubsidized program of Bancoldex in Colombia had positive effects on employment and investment, especially for long-term lending. Using a heterogeneous-agents model calibrated to the US and Brazil, Antunes, Cavalcanti, and Villamil (2015) find that credit subsidy policies have no effect on output and almost no aggregate effects. Our paper complements this literature by providing a direct empirical analysis of the effect of credit policies on productivity through the misallocation channel for a large number of economies. Our findings are consistent with previous results. Public credit reduces misallocation only for financially constrained firms that face financial obstacles. However, it increases misallocation for the rest and, on aggregate, the total effect is very small.

The rest of the paper is organized as follows. Section II presents the theoretical framework used to derive distortions from the data. Section III discusses the econometric methodology. Section IV presents and describes the data. Section V presents the results. Section VI concludes.

II. Measuring Distortions

In Hsieh and Klenow (2009), misallocation arises as a consequence of distortions or wedges that affect heterogeneous firms in an idiosyncratic manner. These wedges, which are akin to taxes, prevent heterogeneous firms from achieving their optimal size, thereby leading to aggregate TFP losses. Below, we briefly explain the quantitative measures of distortions proposed by Hsieh and Klenow (2009), which we will use later in the empirical analysis.

There are $s = 1, \ldots, S$ sectors and M_s firms within each of the S industries. The total final output in sector $s\,(Y_s)$, is a Dixit–Stiglitz aggregator of the output produced by each firm (Y_{si}):

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where σ is the elasticity of substitution between varieties. Each firm's production function is given by a Cobb–Douglas aggregator of capital (K) and labor (L), with individual firm's TFP given by A_{si}:[2]

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{2}$$

There are two distortions or wedges affecting firms. One that affects output or firm size ($\tau_{y,si}$), and another that affects relative factor inputs ($\tau_{k,si}$). Since it is not possible to separately identify wedges that affect capital and labor, we choose to impose the wedge on capital, but this is to be interpreted as a distortion that affects the relative price of capital and labor. As these wedges are firm specific, they will not affect all firms the same way, thus generating differences in capital–labor ratios between firms. With these wedges, the problem of the firm is to choose between K and L to maximize profits (π_{si}):

$$\pi_{si} = \max_{K,L} [(1 - \tau_{y,si}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{k,si}) R K_{si}] \tag{3}$$

where P is the price of the final good, w is the wage rate, and R is the rental price of capital. Since factor markets are competitive, all firms face the same factor prices.

Using the first-order conditions for capital and labor, substituting them in the production function and finding the optimal price for each variety yields the standard result that price is a markup over marginal costs: $P_{si} = \frac{\sigma}{1-\sigma} \left(\frac{R}{\alpha_s}\right)^{\alpha} \left(\frac{w}{1-\alpha_s}\right)^{1-\alpha} \frac{(1+\tau_{k,si})^{\alpha}}{A_{si}(1-\tau_{y,si})}$. With this pricing rule, the quantities of labor demanded and the quantity of output produced by each firm are proportional to their individual TFP and the idiosyncratic distortions or wedges they face. In the absence of distortions, firms' relative shares

[2]The Cobb–Douglas assumption is not innocuous. If the elasticity of substitution between capital and labor differs from 1, then the dispersion of the marginal product of capital, and hence the gains from reallocation, can change substantially. The more that capital and labor are substitutes for one another, the more technologically similar they are and the less important relative factor market distortions will be. Recent evidence suggests that this elasticity significantly differs from unity (see, for example, León–Ledesma, McAdam, and Willman 2010, 2015).

of output and labor would just be a function of A_i. The capital–labor ratio is given by

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{R}\frac{1}{1+\tau_{k,si}} \tag{4}$$

which implies that the idiosyncratic factor market distortion prevents firms from equalizing their capital–labor ratios.

The marginal revenue product of capital is given by $MRPK_{si} = P_{si}MPK_{si}$. Given the definition of MPK, we obtain

$$MRPK_{si} = \alpha_s \frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\frac{1+\tau_{k,si}}{1-\tau_{y,si}} \tag{5}$$

Likewise, TFP revenue (TFPR) is defined as $TFPR_{si} = P_{si}A_{si}$, which, using the definition of prices, yields

$$TFPR_{si} = \frac{\sigma}{\sigma-1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau_{k,si})^{\alpha}}{\left(1-\tau_{y,si}\right)} \tag{6}$$

From equations (5) and (6) above, it is clear that, in the absence of distortions, marginal revenue products of capital and $TFPR_{si}$ would equalize across firms. If a firm has a relatively high A_i, it will attract more capital and labor, until its price falls such that its $TFPR_{si}$ equalizes with that of lower productivity firms. Thus, as discussed below, the dispersion of $MRPK_{si}$ and/or $TFPR_{si}$ is a measure of idiosyncratic distortions affecting firm sizes.

It is also possible to obtain independent measures of size and factor market distortions, which are the ones we will work with as they allow us to separate the effects of access to finance and public credit by type of distortion. From equation (4), we get

$$1+\tau_{k,si} = \frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_{si}} \tag{7}$$

and combining this with (5), we find

$$1-\tau_{y,si} = \frac{\sigma}{\sigma-1}\frac{wL_{si}}{(1-\alpha_s)\,P_{si}Y_{si}} \tag{8}$$

Thus, the factor market distortion measures the firm's relative cost share of labor and capital relative to that for the sector represented by $\alpha_s/(1-\alpha_s)$. The size distortion measures the cost share of labor for the firm relative to that for the sector given by $(1-\alpha_s)$.

What we observe in the data are the $MRPK_{si}$ and $TFPR_{si}$ (and not the MPK_{si} and TFP_{si}) for every firm as we do not observe individual firm prices. This is why Hsieh and Klenow (2009) make an assumption about market structure to infer prices as a function of firm productivity and distortions.

Aggregate TFP in any sector s is defined as TFPR over aggregate prices. Using the final product aggregator, we obtain

$$TFP_s = \frac{TFPR_s}{P_s} = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{9}$$

where $\overline{TFPR}$ is the weighted average of TFPR for all firms in the sector. If all firms were the same (no heterogeneity), the ratio in brackets would disappear. At this point, sectoral (and aggregate) TFP is maximized.[3] That is, aggregate TFP is maximized when there is no dispersion in $TFPR_{si}$. Since by equation (6) the dispersion of TFPR is driven by the dispersion of distortions, then zero dispersion in both factor market and size distortions would imply maximum sectoral TFP.

III. Methodology

Our aim is to uncover the effect of financial access and access to public and private credit on the two measures of firm-level distortions derived from the model used by Hsieh and Klenow (2009): $\log(1+\tau_{k,si})$, and $\log(1-\tau_{y,si})$.[4] Since misallocation depends on the distribution of these measures, we are also interested in uncovering the effect of these variables on their dispersion. To do so, we proceed as follows. We first regress the two measures of distortions on variables measuring financial access, variables measuring access to public credit and private credit, and a set of controls. We will also interact the credit variables with the access-to-finance variables to show whether public and private credit have a different effect for firms that face financial access difficulties. If these variables are not important in affecting the distribution of distortions, they will not be significant. In order to measure whether the different variables increase or decrease the dispersion of distortions, we then use a Fields (2003) decomposition, which we explain below in more detail. This decomposition also allows us to understand better the role of financial variables as some coefficients are not directly interpretable in the initial regressions when we use an instrumental variables approach.

[3] In Hsieh and Klenow (2009), the final economy's output is a Cobb–Douglas aggregator of sectoral outputs $Y = \prod_S Y_s^{\theta_S}$, where θ_S represents sector shares.

[4] In equation (12), we ignore the first term driven by the demand elasticity for the different varieties as it drops as a constant.

Specifically, for the more general case with interaction terms, we run the following cross-sectional regression:

$$\log D_i = \beta_0 + \beta_1 FA_i + \beta_2 PUB_i + \beta_3 PRIV_i + \beta_4 FA_i \times PUB_i + \beta_5 FA_i \times PRIV_i + X_i B + \varepsilon_i \quad (10)$$

where D_i represents the distortion of interest; FA_i is a self-reported financial access difficulty binary variable taking the value of 1 if the firm faces financial obstacles and zero otherwise; PUB_i is a binary variable taking the value of 1 if the firm has access to public credit and zero otherwise; $PRIV_i$ is, similarly, a binary variable for private credit; and X_i is a vector of control variables that includes economy and sector dummies, and other variables.[5] The coefficients β_1 to β_3 give us the direct effect of financial variables, while β_4 and β_5 show how the effect of public and private credit changes when the firm faces financial obstacles. A positive coefficient for the factor market distortion implies that the wedge increases for capital relative to labor. For the size distortion, a positive coefficient implies that the variable reduces the wedge and acts as a size subsidy in the sense that the firm's labor share is higher than the average for its sector. Financial constraints can have either positive or negative effects on size distortions depending on how they affect the activities of the firm. Financial constraints may lead to lower labor costs if firms need working capital to pay wages, or to higher costs if they distort the relative use of capital and labor in the firm given an elasticity of substitution between them.

As explained above, if these variables appear to be significant, then they are drivers of misallocation. However, looking at the coefficients by themselves does not inform us whether these variables lead to an increase or a decrease in the dispersion of distortions. To do so, we look at the Fields (2003) decomposition, which is based on previous contributions by Shorrocks (1982). This decomposition has been used widely in the labor literature to analyze the dispersion of outcome variables such as wages and earnings that can be explained by regressor variables such as education, age, and gender. In our case, we analyze the effect of the different financial variables on the dispersion of the explained part of distortions. We can estimate equation (10) by using ordinary least squares (OLS) or instrumental variable (IV). The resulting predicted distortion can be written as a factor model:

$$\log \widehat{D_i} = \beta_0 + \hat{z}_1 + \hat{z}_2 + \cdots + \hat{z}_k \quad (11)$$

where a hat over a variable denotes its predicted value and $\hat{z}_j = \hat{\beta}_j X_j$ for $j = 1, \ldots,$ k regressors. The Fields (2003) decomposition exploits this factor structure to study the effect of the composite variables $\hat{z}_j$ on the dispersion of the explained part of the

[5] We also experimented using year dummies to control for the year the survey was implemented. The results, however, were not affected by their inclusion.

distortion. That is, it will tell us the percentage increase or decrease in the dispersion of the predicted distortion that is explained by each of the regressors. This allows us to assess the effect of financial variables on misallocation directly.

The main problem with estimating equation (10) by OLS is that access to public or private credit may not be an exogenous treatment. Receiving credit from both types of institutions may depend on unobserved factors that also affect observed distortions, leading to correlation between the credit variables and the error term. For this reason, we also run regressions instrumentalizing both the PUB_i and $PRIV_i$ binary variables.[6] In order to do so, we first run a probit model where we project the variables on a set of instruments plus the controls. We cannot, however, use the fitted values of this regression on a second stage due to the problem of "forbidden regression" as explained by Angrist and Pischke (2009). This happens because the conditional expectation function of the first stage is nonlinear. To get around this problem, we follow Wooldridge (2010) and proceed using the following steps:

(i) Estimate a probit of the determinants of the credit variables using a set of instruments h_i and the control variables X_i. Obtain the fitted values $\widehat{P_i}$.

(ii) Regress P_i on $\widehat{P_i}$ and the control variables X_i, not on the instruments. Obtain the second-stage fitted values $\widehat{\widehat{P}}$.

(iii) Regress D_i on X_i and the second-stage fitted values $\widehat{\widehat{P_i}}$.

Since $\widehat{\widehat{P}}$ now comes from an OLS regression, the problem of the nonlinear conditional expectation function has been eliminated. In our case, however, we also have interaction terms between FA_i and the two instrumentalized credit variables. Interaction variables also suffer from the same forbidden regression problem mentioned above. In order to address this, we follow a similar procedure. We run a first-stage probit and obtain $\widehat{P_i}$. We then calculate $\widehat{P_i} \times FA_i$. We regress $P_i \times FA_i$ on $\widehat{P_i} \times FA_i$ and the exogenous controls to obtain $\widehat{\widehat{P_i} \times FA_i}$. We then regress the distortion variables on $\widehat{\widehat{P_i}}$, $\widehat{\widehat{P_i} \times FA_i}$, and the other controls. This gives us consistent standard errors and unbiased estimates and allows us to carry out the Fields (2003) decomposition. The coefficients on the instrumentalized variables cannot be interpreted the same way as the coefficients of the original binary variables since they are now continuous. However, the decomposition of the dispersion of the distortions still has the same interpretation. This is the added advantage of this decomposition.

[6]The financial access variable is a self-declared variable in the survey. Since there is no a priori reason for firms to declare financial access difficulties to surveyors, we believe it is safe to treat it as exogenous.

IV. Data and Descriptive Statistics

We use firm-level survey data from the World Bank's Enterprise Surveys for the period 2006–2014. This is a stratified survey of firms containing financial and business environment information. The data are purely cross-sectional. Some economies have been surveyed more than once during the review period, so we keep the data for the survey year with more available observations in order not to bias the results by weighting some economies twice. The original data contains results from 134 surveys and a total of 61,669 firms. However, this number was considerably reduced in the data-cleaning process (described below) and because of the lack of availability of some of the credit variables required in the analysis. Since we do not have price data for each firm, we are working with revenue-based measures as discussed in the model used by Hsieh and Klenow (2009). Data are in local currency units for the survey year. We do not transform them into a common currency since the measures we use are ratios and shares rather than absolute values. We calculate the variables of interest as follows:

(i) Output is measured as value added (VA). This is calculated as total annual sales minus the cost of raw materials and intermediate goods.

(ii) The number of workers (L) is the total number of full-time employees adjusted for temporary workers.

(iii) Capital (K) is defined as the net book value of machinery, equipment, land, and buildings.

(iv) Total wage bill (WTOT) corresponds to total wages, salaries, and bonuses paid.

(v) Labor productivity is VA/L.

We drop firms for which either VA, K, or WTOT are negative. We are then left with 23,023 firms and 45 economies. We also dropped any economy for which there are less than 150 firms in the sample. In many of the specifications used below, however, the lack of availability of some of the credit variables and variables used as instruments in the first-stage probit regressions leaves us with approximately 14,800 firms.

Table 1 presents the list of economies, the number of firms, and their distribution by size when we use the sample of 23,023 firms for 45 economies. Size is defined as "small" for firms with fewer than 20 employees, "medium" for firms with between 20 and 99 employees, and "large" for firms with more than 100

Table 1. **Number of Firms and Size Distribution**

		Distribution by Number of Employees (ratio)					Distribution by Number of Employees (ratio)		
	No.	**Small (<20)**	**Medium (20−100)**	**Large (>100)**		**No.**	**Small (<20)**	**Medium (20−100)**	**Large (>100)**
Angola	173	0.85	0.13	0.02	Mali	247	0.79	0.19	0.02
Argentina	532	0.25	0.40	0.35	Mexico	965	0.33	0.34	0.33
Bangladesh	1,039	0.28	0.38	0.35	Mozambique	272	0.63	0.31	0.06
Bolivia	198	0.47	0.37	0.15	Nepal	172	0.32	0.47	0.21
Brazil	925	0.34	0.45	0.21	Nicaragua	197	0.59	0.34	0.07
Bulgaria	362	0.31	0.47	0.22	Nigeria	875	0.68	0.28	0.04
Chile	572	0.30	0.41	0.30	Peru	472	0.24	0.40	0.36
PRC	1,327	0.13	0.43	0.44	Philippines	401	0.22	0.47	0.31
Colombia	545	0.33	0.36	0.31	Russian Federation	438	0.36	0.41	0.23
Costa Rica	172	0.34	0.44	0.22					
Croatia	209	0.34	0.33	0.33	Senegal	209	0.76	0.17	0.07
Ecuador	222	0.41	0.37	0.22	South Africa	644	0.34	0.40	0.26
Egypt	1,299	0.38	0.40	0.22	Sri Lanka	231	0.51	0.29	0.20
El Salvador	282	0.35	0.37	0.28	Sweden	228	0.28	0.52	0.21
Ghana	261	0.64	0.26	0.11	Tanzania	236	0.49	0.35	0.17
Guatemala	244	0.40	0.37	0.23	Tunisia	265	0.18	0.45	0.37
Honduras	184	0.52	0.30	0.18	Turkey	424	0.23	0.41	0.36
India	4,586	0.29	0.46	0.25	Uganda	253	0.58	0.35	0.07
Indonesia	536	0.46	0.29	0.25	Ukraine	245	0.47	0.35	0.18
Iraq	452	0.76	0.23	0.01	Uruguay	159	0.45	0.45	0.10
Jordan	234	0.39	0.33	0.28	Viet Nam	595	0.14	0.41	0.45
Kenya	208	0.27	0.38	0.36	Zambia	279	0.46	0.37	0.17
Lao PDR	311	0.47	0.36	0.17	Zimbabwe	343	0.35	0.38	0.27
					Total	**23,023**	**0.36**	**0.39**	**0.25**

Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Source: Authors' compilation.

employees. There are nine Asian economies in the sample. The sample is dominated by Bangladesh, the PRC, Egypt, and India. While the sample mainly comprises small and medium firms, large firms represent a sizable 25% of the total. Given the prevalence of small firms in these economies, large firms may be overrepresented. The World Bank argues that this is the case since larger firms tend to have a larger impact on employment creation.

The credit and access-to-finance variables also come from the surveys. Firms were asked to answer the following question: "How much of an obstacle is financial access for the operation of the firm?" Firms then choose between "no obstacle," "minor obstacle," "moderate obstacle," "major obstacle," and "very severe obstacle." We translate these into a numeric, binomial variable taking the value of zero for no obstacle, minor, and moderate obstacle; and 1 for major and very severe obstacle. We also do a robustness check by classifying moderate obstacle as 1 rather than zero. This variable is used as a measure of financial access obstacles (FA_i), which will then be interacted with indicators of the type of credit available.

Firms were also asked whether they currently have a line of credit. If so, they were asked the following question: "Is this credit provided by a state-owned bank or a private credit bank?" We use these variables as a proxy for access to public and private credit, which are our PUB_i and $PRIV_i$ variables, respectively. Ideally, such variable should account for the amount of the firm's capital financed by both types of institutions. However, this measure is only available for a very small number of firms. Thus, this variable is taken as a proxy for being able to access either type of credit. The variables public credit (PUB_i) and private credit ($PRIV_i$) are binary variables that take the value of 1 if firms have access to a public or a private line of credit and zero otherwise.

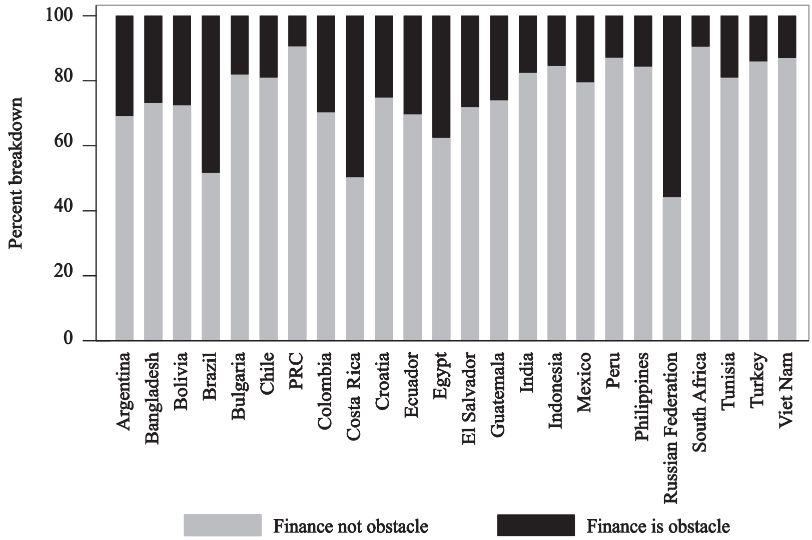
We also use a set of control variables related to other types of obstacles to the operation of firms. These obstacles are measured as binary variables just like the access-to-credit variable. These obstacles can be classified into the following categories: infrastructure (transportation, electricity); goods markets (trade regulations, informal sector); taxation and licensing; insecurity (political instability, corruption, theft, corruption, and courts); and labor markets (regulations and skill inadequacy). These obstacles can affect the optimal size of firms, and hence the dispersion of their marginal products, and can affect different firms heterogeneously and act as wedges that prevent firms from growing to their optimal size.[7]

Finally, we make use of a set of instruments for the first stage of the IV regressions. These include (i) a set of five dummies for the size of the city where the firm operates (each dummy takes the value of 1 for a particular population size range), (ii) the percentage of foreign ownership of the firm, and (iii) the percentage of sales of the firm going to foreign markets. We also experimented with other potential instruments including firm age, legal status of the firm, and percentage of capital held by the main owner of the firm, among others. However, none of these appeared to be significant in the first stage. We will explain below the instruments used for each of the public and private credit binary variables.

Figure 1 shows the percentage of firms in each economy that declare that finance is an obstacle. The economies where firms most commonly declare financial access problems are mainly African economies with a lower level of financial development, followed by mainly Latin American economies. In economies like the PRC and India, the share declaring financial access problems is much lower, which is generally also true for all other Asian economies in the sample with the exception of Bangladesh and Nepal. Figure 2 shows the shares of firms in each economy that receive a credit line from either public or private institutions. The sum of PUB_i and $PRIV_i$ does not cover all firms in the sample since a sizable proportion of them do not have a credit line. The PRC, India, the Lao People's Democratic Republic, and Viet Nam are the economies with the largest shares of firms with access to public credit lines. In general, Asian economies tend to have

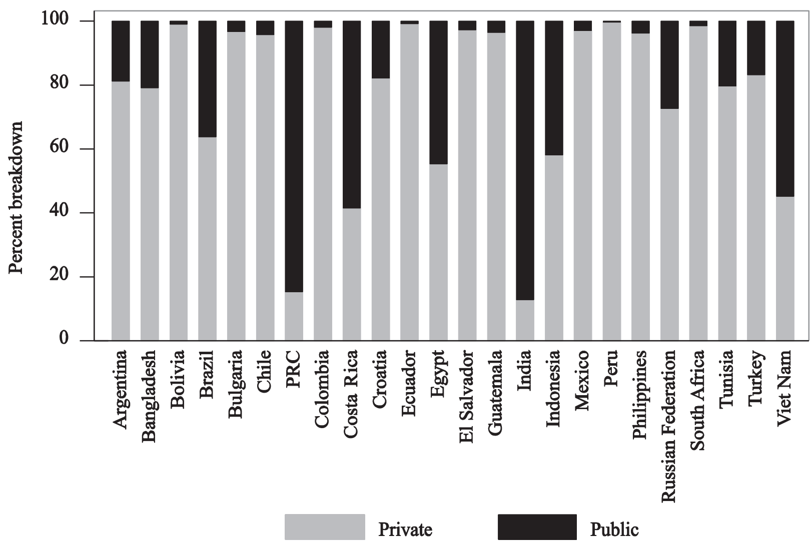
[7]See León–Ledesma (2016) for a detailed analysis of the role of these obstacles in driving misallocation.

Figure 1. **Percentage of Firms Declaring Finance is an Obstacle to Operations**



PRC = People's Republic of China.
Source: Authors' calculations based on data from World Bank. Enterprise Surveys and Indicator Surveys Sampling Methodology. www.enterprisesurveys.org

Figure 2. **Percentage of Firms Receiving Loan from Public Institutions**



PRC = People's Republic of China.
Source: Authors' calculations based on data from World Bank. Enterprise Surveys and Indicator Surveys Sampling Methodology. www.enterprisesurveys.org

a larger proportion of firms with access to public credit, which is consistent with the presence of directed credit institutions. Outside this group, economies such as Brazil, Egypt, and Russian Federation have a large proportion of firms with access to public credit as well, which is (again) consistent with the existence of state-owned lenders in the market.

Table 2 shows the distribution of public credit by firm size in each economy.[8] On average, it appears that public credit is slightly biased toward medium and large firms, and against small firms, when compared to the distribution of all firms in Table 1. This varies substantially by economy, but it is evident for large economies with an important element of public lending such as the PRC, India, and Russian Federation. For economies with a low prevalence of public credit lines, all public credit appears concentrated in a single size category.

Table 3 shows how the three possible credit outcomes (public, private, or no credit) are distributed in each economy for firms that face financial obstacles and those that do not. It is quite striking that, on average, the proportions are almost the same for both categories of firms. Neither public nor private credit appears to be more prevalent for firms that do not face financial obstacles. Of course, this result compounds demand and supply effects, so we cannot extract meaningful structural interpretations. Interestingly, this appears to be the case for most economies in the sample.

V. Results

We now proceed to analyze the regression results. The dependent variables measuring distortions were calculated in equations (7) and (8) and then logged. To calculate α_s, we averaged the capital share for firms by economy and sector, and trimmed the upper and lower 5% to smooth out the effect of outliers. Unfortunately, we only know a firm's sector at a high level of aggregation; there are a total of 15 sectors for both industry and services, with agricultural firms being excluded. Although it would be desirable to obtain capital shares for a larger number of sectors to obtain measures of misallocation, this will not affect the regression results as we include sector dummies that capture sector fixed effects. We then obtain the standard deviation of the two distortions for each sector and average them by economy. The average results for all economies are displayed in Table 4. The results show a high level of dispersion for both measures. Consistent with other studies—such as Hsieh and Klenow (2009) and Ha, Kiyota, and Yamanouchi (2016)—the factor market distortion is larger than the size distortion. There is also wide variability between economies. Angola displays the lowest size distortion and the Philippines displays the largest. For factor market distortions, South Africa displays the lowest and Sri Lanka displays the largest dispersions.

[8]There are only 39 economies out of the 45-economy sample for which public credit information is available.

Table 2. **Size Distribution of Firms Receiving Public Credit**

	Size Distribution by Number of Employees		
	Small (<20)	**Medium (20–100)**	**Large (>100)**
Argentina	16%	44%	41%
Bangladesh	23%	40%	36%
Bolivia	100%	0%	0%
Brazil	37%	44%	19%
Bulgaria	20%	60%	20%
Chile	42%	32%	26%
PRC	4%	35%	61%
Colombia	25%	63%	13%
Costa Rica	35%	58%	6%
Croatia	26%	26%	48%
Ecuador	0%	100%	0%
Egypt	29%	39%	32%
El Salvador	60%	20%	20%
Ghana	32%	37%	32%
Guatemala	50%	50%	0%
Honduras	100%	0%	0%
India	23%	49%	28%
Indonesia	35%	29%	36%
Iraq	70%	20%	10%
Kenya	13%	38%	50%
Lao PDR	38%	38%	24%
Mali	0%	100%	0%
Mexico	64%	29%	7%
Mozambique	0%	100%	0%
Nepal	45%	45%	9%
Peru	100%	0%	0%
Philippines	33%	67%	0%
Russian Federation	18%	42%	40%
South Africa	0%	0%	100%
Sri Lanka	46%	21%	33%
Sweden	50%	33%	17%
Tanzania	45%	27%	27%
Tunisia	20%	43%	37%
Turkey	25%	60%	15%
Ukraine	33%	33%	33%
Uruguay	42%	46%	13%
Viet Nam	12%	38%	50%
Zambia	29%	43%	29%
Zimbabwe	33%	33%	33%
Total	**23%**	**44%**	**33%**

Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Source: Authors' compilation.

The results of the regression analysis are presented in Tables 5 and 6 for τ_k and τ_y, respectively. We use as controls the economy and sector dummies, as well as a set of other binary obstacle variables that were explained in the previous section. The tables present the results with and without interaction terms for the OLS and IV regressions.

Table 3. **Allocation of Public and Private Loans by Financial Obstacles**

	If credit is an obstacle, do you have. . .?			**If credit is not an obstacle, do you have. . .?**		
	Private Credit	**Public Credit**	**No Credit**	**Private Credit**	**Public Credit**	**No Credit**
Angola	4%	0%	96%	0%	0%	100%
Argentina	46%	11%	43%	56%	12%	32%
Bangladesh	35%	14%	52%	37%	8%	55%
Bolivia	53%	0%	47%	55%	1%	44%
Brazil	42%	23%	36%	44%	26%	30%
Bulgaria	46%	0%	54%	41%	2%	57%
Chile	74%	3%	23%	77%	3%	19%
PRC	7%	58%	36%	5%	25%	71%
Colombia	72%	2%	26%	78%	1%	21%
Costa Rica	24%	39%	37%	27%	33%	40%
Croatia	69%	17%	14%	57%	12%	31%
Ecuador	64%	0%	36%	56%	1%	44%
Egypt	6%	8%	86%	6%	3%	91%
El Salvador	59%	5%	36%	68%	1%	32%
Ghana	11%	6%	83%	9%	11%	80%
Guatemala	48%	2%	50%	46%	2%	52%
Honduras	48%	0%	52%	51%	1%	47%
India	4%	35%	61%	4%	28%	68%
Indonesia	17%	17%	66%	19%	13%	68%
Iraq	3%	2%	95%	2%	2%	95%
Jordan	19%	0%	81%	30%	0%	70%
Kenya	43%	4%	52%	43%	4%	54%
Lao PDR	15%	25%	60%	3%	6%	91%
Mali	2%	1%	97%	7%	2%	91%
Mexico	44%	2%	54%	51%	1%	48%
Mozambique	7%	1%	92%	8%	0%	92%
Nepal	39%	15%	46%	31%	3%	67%
Nicaragua	31%	0%	69%	37%	0%	63%
Peru	72%	1%	26%	87%	0%	13%
Philippines	51%	2%	47%	37%	1%	61%
Russian Federation	23%	12%	65%	20%	11%	69%
Senegal	13%	0%	87%	10%	0%	90%
South Africa	22%	0%	78%	34%	1%	65%
Sri Lanka	31%	11%	58%	32%	10%	58%
Sweden	33%	0%	67%	27%	3%	70%
Tanzania	18%	5%	76%	19%	4%	77%
Tunisia	45%	15%	40%	44%	11%	45%
Turkey	69%	12%	18%	55%	11%	34%
Uganda	13%	0%	87%	20%	0%	80%
Ukraine	15%	0%	85%	20%	2%	78%
Uruguay	33%	21%	47%	35%	13%	52%
Viet Nam	30%	30%	40%	31%	38%	32%
Zambia	15%	2%	83%	13%	3%	85%
Zimbabwe	18%	1%	81%	9%	1%	90%
Total	**26%**	**12%**	**62%**	**27%**	**13%**	**60%**

Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Source: Authors' compilation.

Table 4. **Misallocation Measures: Dispersion of Distortions**

Variable	Mean	Standard Deviation	Min	Max
StDev(τ_y)	0.902	0.184	0.478	1.255
StDev(τ_k)	1.252	0.190	0.843	1.604

Source: Authors' calculations.

The instruments used for the first-stage probit for the public credit variable are as follows. First, a set of dummies is created for the city in which the firm is located, taking the value of 1 for a particular city size and zero otherwise. The sizes are "capital city," "more than 1 million," "between 250,000 and 1 million," "between 50,000 and 250,000," and "less than 50,000." The second instrument used is a variable measuring the percentage of foreign ownership in the firm. Finally, we use the rest of the control variables included in the regression. The set of city dummies are undoubtedly exogenous and unlikely to be correlated with determinants of distortions other than access to infrastructure, which we control for. We would also expect foreign ownership to reduce access to public credit as local firms are normally given preferential treatment.

For the first-stage probit for the private credit variable, we use the same city-size dummies plus a variable measuring the percentage of sales going to international markets (exports). It is likely that firms located closer to financial centers and with more diversified and/or larger markets (exporters) will have better access to private credit. Our first-stage probits, which are available upon request, show that all the instruments are significant, the sign of their coefficients are as expected, and the regression is well behaved in general. We also experimented with a wider set of instruments, but their correlation with the endogenous variables proved to be too weak to identify a causal effect.

The results in Table 5 show that several variables are significant drivers of the factor market distortion τ_k. This is especially the case for our finance-related variables. The first result is that financial obstacles appear to increase the relative cost of capital by close to 18% in all specifications as expected. This is also a very significant effect. In the OLS regressions, access to both private and public loans appears to significantly reduce the distortion. The interaction term appears to be insignificant for private credit but significant for public credit. The negative effect of public credit on the distortion appears to be stronger for firms that face financial obstacles than for those that do not. However, as seen in Table 3, the distribution of public credit does not appear to change significantly between these two types of firms. Therefore, the total effect on the distribution of the distortion can only be inferred from the Fields (2003) decomposition. The IV regressions, however, tell a slightly different story. The interpretation of the public and private loan variables cannot be done the same way since the variables are now continuous. In the specification with no interactions, having access to a private credit line reduces the distortion, while the effect of the public credit variable is not significant. The interaction variables

Table 5. **Regression Results for Factor Market Distortions (τ_k)**

	OLS Regressions		IV Regressions	
	(1)	**(2)**	**(3)**	**(4)**
Access to finance	0.184*	0.206*	0.175*	0.175**
	(7.36)	(6.68)	(6.27)	(3.13)
Private loan (yes = 1)	−0.120*	−0.125*	−2.418*	−2.540*
	(−4.30)	(−3.97)	(−4.51)	(−4.71)
Public loan (yes = 1)	−0.113*	−0.0693***	0.497	0.608***
	(−3.66)	(−2.11)	(1.82)	(2.20)
Access to finance × Private loan		0.00938		0.234***
		(0.18)		(2.00)
Access to finance × Public loan		−0.200**		−0.415***
		(−2.70)		(−2.16)
Electricity	−0.0335	−0.0334	−0.0186	−0.0186
	(−1.40)	(−1.40)	(−0.71)	(−0.72)
Transportation	−0.0231	−0.0231	0.00365	0.00375
	(−0.82)	(−0.82)	(0.11)	(0.11)
Customs and trade regulations	−0.0982**	−0.0972**	0.0131	0.0158
	(−2.97)	(−2.94)	(0.29)	(0.35)
Informal sector	0.0679**	0.0675**	0.0364	0.0359
	(2.69)	(2.68)	(1.32)	(1.30)
Access to land	0.00510	0.00663	−0.0754***	−0.0665
	(0.17)	(0.22)	(−2.17)	(−1.91)
Crime, theft	−0.0367	−0.0372	−0.0622	−0.0641
	(−1.18)	(−1.19)	(−1.77)	(−1.82)
Tax rates	−0.0465	−0.0468	−0.0659***	−0.0670***
	(−1.85)	(−1.86)	(−2.25)	(−2.29)
Tax administration	0.0525	0.0530	0.0805***	0.0830***
	(1.77)	(1.78)	(2.35)	(2.42)
Business licensing	−0.0326	−0.0327	−0.0927***	−0.0917***
	(−1.06)	(−1.06)	(−2.50)	(−2.47)
Political instability	0.0176	0.0183	−0.0190	−0.0175
	(0.59)	(0.61)	(−0.59)	(−0.54)
Corruption	−0.0371	−0.0380	−0.0184	−0.0186
	(−1.44)	(−1.47)	(−0.60)	(−0.61)
Courts	0.0808***	0.0810***	0.0875***	0.0826***
	(2.45)	(2.45)	(2.31)	(2.18)
Labor regulations	0.0178	0.0181	0.105**	0.104**
	(0.54)	(0.55)	(2.79)	(2.75)
Inadequate education workers	0.0328	0.0321	0.110**	0.108**
	(1.12)	(1.10)	(3.10)	(3.04)
Country dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Constant	−0.539***	−0.547***	0.0451	0.0577
	(−2.03)	(−2.05)	(0.24)	(0.31)
N	18,025	18,025	14,828	14,828
R^2	0.014	0.015	0.013	0.014

IV = instrumental variable, OLS = ordinary least squares.
Notes: *** = 10% level of significance, ** = 5% level of significance, * = 1% level of significance. t statistics in parentheses. Heteroscedasticity-consistent standard errors. See text for the IV procedure implemented using a first-stage probit for public and private credit.
Source: Authors' calculations.

Table 6. **Regression Results for Factor Market Distortions (τ_y)**

	OLS Regressions		IV Regressions	
	(1)	**(2)**	**(3)**	**(4)**
Access to finance	0.133*	0.146*	0.125*	0.104***
	(7.27)	(6.58)	(6.08)	(2.51)
Private loan (yes = 1)	−0.083*	−0.086*	−1.720*	−1.802*
	(−3.97)	(−3.70)	(−4.35)	(−4.54)
Public loan (yes = 1)	−0.0728**	−0.0455	0.326	0.367
	(−3.11)	(−1.85)	(1.63)	(1.80)
Access to finance × Private loan		0.00946		0.166
		(0.25)		(1.93)
Access to finance × Public loan		−0.126***		−0.152
		(−2.18)		(−1.07)
Electricity	−0.0220	−0.0220	−0.0128	−0.0129
	(−1.25)	(−1.25)	(−0.67)	(−0.67)
Transportation	−0.00757	−0.00755	0.0186	0.0188
	(−0.37)	(−0.37)	(0.75)	(0.76)
Customs and trade regulations	−0.0716**	−0.0710**	0.00625	0.00707
	(−2.87)	(−2.85)	(0.19)	(0.21)
Informal sector	0.0453***	0.0451***	0.0224	0.0224
	(2.50)	(2.49)	(1.11)	(1.11)
Access to land	0.00463	0.00567	−0.0537***	−0.0480
	(0.21)	(0.26)	(−2.10)	(−1.87)
Crime, theft	−0.0325	−0.0328	−0.0530***	−0.0538***
	(−1.40)	(−1.42)	(−2.04)	(−2.08)
Tax rates	−0.0221	−0.0223	−0.0376	−0.0384
	(−1.17)	(−1.17)	(−1.75)	(−1.78)
Tax administration	0.0346	0.0349	0.0520***	0.0531***
	(1.55)	(1.57)	(2.06)	(2.10)
Business licensing	−0.0293	−0.0293	−0.0737**	−0.0728**
	(−1.27)	(−1.27)	(−2.70)	(−2.67)
Political instability	0.00970	0.0101	−0.0188	−0.0185
	(0.42)	(0.44)	(−0.79)	(−0.78)
Corruption	−0.0362	−0.0367	−0.0192	−0.0187
	(−1.89)	(−1.92)	(−0.86)	(−0.83)
Courts	0.0694**	0.0695**	0.0739**	0.0707***
	(2.86)	(2.86)	(2.65)	(2.54)
Labor regulations	0.0125	0.0126	0.0728**	0.0718**
	(0.51)	(0.52)	(2.63)	(2.59)
Inadequate education workers	0.0264	0.0259	0.0784**	0.0773**
	(1.21)	(1.19)	(3.01)	(2.96)
Country dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Constant	−0.379***	−0.383***	−0.05	−0.04
	(−2.20)	(−2.22)	(−0.39)	(−0.30)
N	18,027	18,027	14,828	14,828
R^2	0.02	0.02	0.02	0.02

IV = instrumental variable, OLS = ordinary least squares.
Notes: *** = 10% level of significance, ** = 5% level of significance, * = 1% level of significance. t statistics in parentheses. Heteroscedasticity-consistent standard errors. See text for the IV procedure implemented using a first-stage probit for public and private credit.
Source: Authors' calculations.

in column (4) show that public credit now reduces the distortion for firms that face financial obstacles. The total effect for these firms is, however, still negative. For private loans, the effect is the opposite; it reduces the distortion more for firms that do not report financial obstacles. Overall, the regression is jointly significant. However, the variables explain only a small part of the variation of the endogenous variable as shown by the R^2 coefficient.

For the size distortion, the results are presented in Table 6. Lack of access to finance acts as a size subsidy in the sense that it increases the cost share of labor in value added. This, however, may well be the consequence of a lack of access to finance leading to higher labor intensity due to a lack of access to capital. Public and private credit have the opposite effects as were expected from the OLS regressions. The significant result for the public credit variable disappears when we introduce the interaction with financial access in the IV regressions. However, in the OLS regression, access to a public loan for firms that face financial difficulties has a significantly negative effect; it acts as a size tax. Turning to the IV regressions, the only variable that appears to be significant is access to private credit, which reduces the cost share of labor. Public credit has a positive effect, but it is not significantly different from zero. The interaction terms are not significant either. Hence, being the recipient of a public or a private loan when the firm faces financial obstacles does not appear to be significantly different from when they do not face financial obstacles. Overall, the results are not very conclusive beyond the fact that obstacles to finance and accessing a private loan are significant drivers of size distortions.

Finally, we turn to the Fields (2003) decompositions for both distortions in Tables 7 and 8. The results show the percentage of the explained part of the dispersion of distortions to which each variable contributes. This contribution can be positive if the variable increases the dispersion of the distortion, or negative if it reduces it. These results should be seen in conjunction with the regression results to analyze whether these effects are significant. The sum of the contributions of the variables, including economy and sector dummies, is 100 as we are looking at the explained part. We focus here on the IV regression results in columns (3) and (4), although we also present the results from the OLS regressions.

For the factor market distortion, all obstacles explain almost half of the dispersion of the distortion, the other half is explained mainly by economy dummies. Of the obstacles, the main driver is access to finance. Financial obstacles increase the dispersion of τ_k, leading to misallocation. Being the recipient of a public loan has a small positive effect on dispersion as well. For firms facing financial obstacles, the effect is negative. However, the magnitude of the effect is very small in comparison with not having a loan. For private loans, the effect is positive. The effect of having a private loan for firms that face financial obstacles is positive and sizable. Private loans appear to increase the dispersion of the distortion, thus their allocation across firms increases allocative inefficiency. This is indicative of possible distortions in private credit markets. Public credit, which is designed to allow firms with viable investment

Table 7. **Contribution of Variables to the Explained Dispersion of τ_k (%)**

	OLS Regressions		IV Regressions	
	(1)	**(2)**	**(3)**	**(4)**
Access to finance	24.36	26.35	21.68	20.37
Private loan (yes = 1)	7.45	7.47	7.97	7.86
Public loan (yes = 1)	3.55	2.11	0.20	0.23
Access to finance × Private loan		0.20		8.89
Access to finance × Public loan		1.59		−3.70
Electricity	0.48	0.46	0.23	0.22
Transportation	0.13	0.12	−0.04	−0.04
Customs and trade regulations	3.40	3.26	−0.51	−0.57
Informal sector	4.00	3.85	1.73	1.60
Access to land	0.10	0.12	−0.12	−0.10
Crime, theft	0.15	0.15	0.62	0.60
Tax rates	0.98	0.95	1.80	1.72
Tax administration	0.89	0.87	0.81	0.79
Business licensing	0.19	0.18	1.51	1.40
Political instability	−0.35	−0.35	0.47	0.40
Corruption	0.40	0.39	0.36	0.34
Courts	2.55	2.47	3.70	3.28
Labor regulations	0.29	0.28	2.07	1.92
Inadequate education workers	0.73	0.70	2.25	2.07
All obstacles	49.29	51.19	44.74	47.26
Country dummies	48.17	46.41	55.50	53.14
Sector dummies	2.54	2.40	−0.24	−0.41
Total	**100**	**100**	**100**	**100**

IV = instrumental variable, OLS = ordinary least squares.
Source: Authors' calculations.

projects to bypass financial constraints, only reduces the allocative inefficiency of factors of production by a small amount for all firms. It even increases it marginally for firms that do not report facing financial obstacles. Overall, however, the role of public credit in improving aggregate TFP through improved allocation of capital and labor is almost negligible.

A very similar picture arises from the decomposition of τ_y. In this case, access to finance has a smaller effect, and it is being a recipient of a private loan that seems to dominate by increasing substantially the dispersion of the size distortion. Public credit also increases this dispersion, except for firms that face financial obstacles. However, the effect of these interaction variables and the direct effect of public credit is not significant when we look at the regression results. In fact, not having a credit line at all while facing financial obstacles appears to lead to a smaller dispersion of distortions than having a credit line.

Distortions that affect firms in an idiosyncratic way lead to an inefficient allocation of capital and labor, and firm sizes. These distortions, whether generated by market or government failures, may be caused by an inefficient allocation of credit. Our evidence shows that the allocation of both private and public credit leads to an increase in the dispersion of distortions. Public credit only reduces

Table 8. **Contribution of Variables to the Explained Dispersion of τ_y (%)**

	OLS Regressions		IV Regressions	
	(1)	(2)	(3)	(4)
Access to finance	17.71	19.03	15.17	12.25
Private loan (yes = 1)	5.79	5.93	24.96	25.44
Public loan (yes = 1)	1.71	1.05	1.27	1.39
Access to finance × Private loan		0.19		5.81
Access to finance × Public loan		0.79		−1.64
Electricity	0.46	0.45	0.21	0.21
Transportation	0.02	0.02	−0.15	−0.15
Customs and trade regulations	2.65	2.58	−0.29	−0.32
Informal sector	2.40	2.34	0.82	0.80
Access to land	0.08	0.10	0.29	0.25
Crime, theft	0.34	0.33	1.09	1.07
Tax rates	0.44	0.43	1.15	1.14
Tax administration	0.51	0.51	0.09	0.09
Business licensing	0.33	0.32	2.17	2.08
Political instability	−0.41	−0.42	0.96	0.92
Corruption	0.84	0.84	0.61	0.58
Courts	2.28	2.24	3.13	2.92
Labor regulations	0.20	0.20	1.13	1.08
Inadequate education workers	0.48	0.47	0.75	0.72
All obstacles	35.82	37.38	53.36	54.63
Country dummies	61.27	59.83	45.22	44.09
Sector dummies	2.91	2.80	1.42	1.27
Total	**100**	**100**	**100**	**100**

IV = instrumental variable, OLS = ordinary least squares.
Source: Authors' calculations.

this dispersion for firms that face (self-declared) financial obstacles. It is clear that public credit does not appear to compensate for the distortions that exist in private credit markets. However, the bulk of the dispersion of these distortions remains unexplained. Finance appears to be important only when we look at the part of the distortions that we are able to explain with observations. In that sense, our results are consistent with several results in the literature that attribute a minor role to financial access in explaining misallocation.

VI. Conclusions

Misallocation implies that, with the same amount of capital, labor, and firm-level TFP, aggregate TFP can be higher if factors of production were reallocated between firms. Distortions that affect firms in a heterogeneous way lead to suboptimal capital–labor ratios at the firm level and a distribution of firm sizes that is not consistent with the distribution of their TFP. One of the factors that may drive these distortions are financial frictions that prevent viable projects from being financed and allow unviable projects to be financed.

We have studied quantitatively the effect of access to finance to explain the dispersion of factor market and size distortions that drive misallocation. Our focus is not only on the effect of financial obstacles, but also on whether public credit has a significant effect in improving allocation. Directed credit policies through government-owned institutions are very common in many emerging markets and have gained importance in recent decades. Thus, it is important to understand whether government credit has any positive effect on aggregate TFP, and hence per capita income, through an improved allocation of resources.

We use a database of close to 23,000 firms in 45 economies and derive two measures of distortions from the Hsieh and Klenow (2009) model. The first measures factor market distortions that prevent firms from achieving their optimal capital–labor ratio. The second measures size distortions that prevent firms from achieving their optimal size as dictated by their TFP. We then use a regression approach to measure the effect of self-declared access-to-finance obstacles, access to a government-owned bank credit line, and access to a private-owned bank credit line on these two measures of distortions. We instrumentalize the public and private credit line variables to isolate their treatment effect. We then use a regression-based decomposition that allows us to see whether these variables increase or decrease the dispersion of distortions across firms.

Our results show that access-to-finance obstacles increase the dispersion of both factor market distortions and size distortions. Private credit increases the dispersion of both distortions, especially the size distortion. This is not surprising given that it is the existence of informational asymmetries together with underdeveloped financial markets that can lead to an inefficient allocation of private credit. Public credit, on the other hand, has a very small effect. For firms that do not face financial obstacles, it increases slightly the dispersion of both distortions. For firms that face financial obstacles, it decreases slightly the dispersion, but it is not significant in the case of size distortions. However, public credit does not appear to compensate for the distortions that exist in the private credit markets. We thus conclude that public credit does not appear to improve significantly the informational and regulatory frictions that exist in credit markets even among our sample that is dominated by developing economies with lower levels of financial depth. The majority of the dispersion of these distortions remains unexplained. Financial variables appear only to be important in driving the explained part of these distortions and are significant. However, they cannot explain a sizable enough part of them to be considered as the key drivers of misallocation.

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